Emergence Modeling and Economics of Managing Herbicide-Resistant Giant Ragweed (*Ambrosia trifida*) with Crop Rotation

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Jared Jay Goplen

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CHAPTER 1: ECONOMIC PERFORMANCE OF CROP ROTATIONS IN THE PRESENCE OF HERBICIDE-RESISTANT GIANT RAGWEED

1.1 Summary. Economic assessment of alternative crops and crop rotations helps farmers determine those most appropriate for their farms. The objective was to evaluate the economic net return and associated financial risk for crops and crop rotations common to the Midwestern United States, based on two 3-yr experiments in southern Minnesota where herbicide-resistant giant ragweed (*Ambrosia trifida* L.) was present. Crop rotations included corn (*Zea mays* L.), soybean [*Glycine max* L. (Merr.)], wheat (*Triticum aestivum* L.), and alfalfa (*Medicago sativa* L.). Crop rotations were continuous corn (CCC), soybean-corn-corn (SCC), corn-soybean-corn (CSC), soybean-wheat-corn (SWC), soybean-alfalfa-corn (SAC), and alfalfa-alfalfa-corn (AAC). Average crop yields during the study period (2012 to 2015) were utilized along with average prices received and estimated production costs for each crop in Minnesota during this period to evaluate economic net return. Average net return of the SWC, SCC, CCC, CSC, SAC, and AAC rotations was \$11, \$170, \$247, \$258, \$368, and \$919 ha^{-1} yr^{-1}, respectively. In addition to producing greatest net return, the AAC rotation also was stochastically dominant to all other crop rotations for risk-averse decision makers. One or two years of alfalfa stochastically dominated corn, soybean, and wheat, regardless of crop rotation, largely due to more stable alfalfa prices over the study period coupled with above-average yield and lower production costs. These results confirm that rotations containing alfalfa have the potential to provide a substantial economic net return to farmers while mitigating the risk of herbicide-resistant giant ragweed infestations.

1.2 Introduction. Crop rotations have long been the foundation of good agronomic practice and improve the control of weeds, crop diseases, and insect pests (Altieri, 1999; Liebman and Dyck, 1993). Diverse crop rotations also provide a yield-enhancing “rotation effect” compared to less diverse rotations (Crookston et al., 1991; Berzsenyi et al., 2000). Corn and soybean grown in rotation typically outyield their monoculture counterparts, and yield of corn typically is greater when grown in rotation with wheat or alfalfa compared to when it is grown in monoculture (Edwards et al. 1988; Stanger and Lauer 2008). In addition to providing a yield-enhancing effect, diverse crop rotations vary in patterns of resource competition, mechanical weed control, and soil disturbance, resulting in a disruptive environment for specific weed species (Liebman and Dyck, 1993). Weed control benefits of crop rotation are even more valuable when herbicide-resistant weeds are present (Gill and Holmes, 1997).

Giant ragweed is one of the most competitive and problematic weeds affecting crop production in the Midwestern United States and has recently developed resistance to multiple herbicide sites of action, including acetolactate synthase and 5-enolpyruvylshikimate-3-phosphate synthase inhibitors (Webster et al., 1994; Heap, 2016). Crop rotations with multiple years of alfalfa reduce herbicide-resistant giant ragweed emergence while maintaining a similar level of seed bank depletion as other crop rotations common to the Midwestern United States (Goplen et al., 2016b). The frequent harvests of alfalfa also reduce populations of annual weeds adapted to corn and soybean by reducing weed seed production and providing year-round ground cover favorable for insects, rodents, and fungi that consume weed seeds (Westerman et al., 2005; Meiss et al., 2010a; 2010b). Incorporating wheat into crop rotations also provides weed control benefits by being planted earlier than corn and soybean and at greater plant densities in narrow rows, causing it to be more competitive with early-emerging weeds (Swanton et al., 1999). Wheat also allows the use of herbicides with modes of action that are effective on herbicide-resistant giant ragweed, reducing the likelihood of herbicide-resistant giant ragweed escapes.

Although more diverse crop rotations provide weed control benefits and reduce the risk of developing herbicide-resistant weeds, the crop rotation used in a given field often is dictated by profit potential rather than ease of herbicide-resistant weed management (Beckie, 2006). Herbicide-resistant weeds increase the cost of crop production due to specialized management and therefore have potential to alter the economic net return associated with particular crops and crop rotations (Mueller et al., 2005; Norsworthy et al., 2012).

There is a need to compare economic net return and financial risk of crop rotations common to the Midwestern United States, a region where herbicide-resistant giant ragweed is widespread (Regnier et al., 2016). The objectives were to evaluate the crop yields and economic net return for multiple crop rotations and determine the most risk-averse crops and crop rotations using stochastic dominance analysis.

1.3 Materials and Methods

1.3.1 Crop Rotation Experiments. In 2012 and 2013, two replicated experiments were established at different sites near Rochester, MN (43°54’20.5”N, 92°33’, 55.1”W and 43°54’20.7”N, 92°33’, 40.3”W). The research sites had known populations of giant ragweed resistant to 5-enolpyruvylshikimate-3-phosphate synthase and acetolactate synthase inhibitor herbicides. Each experiment evaluated six crop rotations in a randomized complete block design with four replications: CCC, SCC, CSC, SWC, SAC, and AAC. These experiments, described in Goplen et al.

(2016b), monitored giant ragweed seed bank depletion and emergence in each crop rotation to assess the weed control benefits associated with each crop rotation. Fertilizer P, K, and S were applied to meet crop requirements according to University of Minnesota guidelines (Kaiser et al., 2011).

From 2012 to 2015, grain yields of corn, soybean, and wheat were determined by harvesting two 1.5 × 9 m areas, three 1.5 × 6 m areas, and three 1.5 × 9.1 m areas, respectively. Grain subsamples (~1 kg) were dried in a forced-air oven at 60ºC until constant mass to determine moisture. Corn, soybean, and wheat yields were adjusted to 155, 130, and 135 g kg^{-1}moisture content, respectively. To determine wheat straw yield, four samples of whole wheat plants were cut at 10 cm above the soil surface from a 0.76 × 0.91 m area within each plot prior to grain harvest. Whole samples were dried at 60ºC in a forced-air oven until constant mass and threshed using a stationary thresher to separate grain from straw to determine straw dry matter.

Alfalfa yield was measured by harvesting three 0.9 × 6.4 m areas per plot and adjusted to a dry matter basis by drying a subsample (~1 kg) at 60ºC in a forced-air oven until constant mass. In the SAC rotation, where only a single year of alfalfa was grown, alfalfa was harvested three times on approximately 30-d intervals beginning in July. In the AAC rotation, alfalfa was cut twice during the seedling year on approximately 30-d intervals beginning in July, and four times during the subsequent year. Harvests occurred when alfalfa was at the early flower stage of development (Fick and Mueller, 1999). Alfalfa relative feed value was estimated using near infrared spectroscopy measurements of acid detergent fiber and neutral detergent fiber according to Jeranyama and Garcia (2004).

1.3.2 Economic Analysis. Economic net return of each crop rotation was determined by monitoring all inputs and outputs of the crop rotations during all 3 yr of the rotations. Production costs of each rotation were calculated using average costs from 2012 to 2015, in accordance with Zacharias and Grube (1984). Seed and pesticide costs were obtained from local agribusinesses and fertilizer costs were the average in Minnesota reported by USDA-National Agricultural Statistics Service (2016) during the study period. Machinery and field operation costs were obtained from Lazarus (2015) and land rental costs were set to the county average reported by Hachfeld et al. (2015). Grain drying costs for corn, soybean, and wheat were calculated based on values reported by Lazarus (2014). The giant ragweed emergence component of this study required that seed production of giant ragweed be prevented, and resulted in hand weeding of several crops in most years to fully prevent giant ragweed seed production (Goplen et al., 2016b). Although hand weeding was conducted, the costs associated with it were not included in this analysis.

Revenue was calculated for each plot as the product of crop yield and average yearly price in Minnesota for each growing season from 2012 to 2015 to produce a range in revenue values for each crop rotation and crop for use in stochastic dominance analysis (Table 1-1). Average net return for each plot was calculated as the difference between total revenue and production costs. Average grain prices received each year for corn, soybean, and wheat in Minnesota were obtained from USDA-National Agricultural Statistics Service (2016). Average alfalfa hay and wheat straw prices for each year were obtained from regional auction reports (Szafranski and Martens, 2016). All alfalfa harvested in this study had a relative feed value greater than 150. Since quality alfalfa typically receives a price premium, the average of alfalfa prices with relative feed values greater than 150 was used to determine alfalfa price.

Stochastic dominance analyses were used to compare the cumulative distribution function (CDF) of net return for each crop rotation as the basis for estimating economic risk. Crop rotations and individual crops regardless of rotation were analyzed using both first degree stochastic dominance (FSD) and second degree stochastic dominance (SSD). In both cases, stochastic dominance was determined by comparing the CDFs among rotations or crops. First order stochastic dominance assumes that decision makers prefer greater return over lesser return and is established when all values of a given CDF are greater than those of another CDF. Treatments were considered indifferent if the CDFs cross at any point. Second degree stochastic dominance has an additional assumption that decision makers are also risk averse. A treatment stochastically dominates another by SSD if the area under the CDF is less than or equal to that of another treatment at all net return values (Hardaker et al., 2004).

To evaluate economic net return among crop rotations and corn grain yield in the third rotation-year when all rotations were planted to corn, net return and corn grain yield were analyzed using the MIXED procedure of SAS (SAS Institute, 2012). Crop rotation was considered a fixed effect, and experiment, block (nested within experiment), subsampling, and interactions with experiment, block, and subsampling were considered random effects. Mean comparisons were made using Fisher's protected LSD test ($P \leq 0.05$).

1.4 Results and Discussion

1.4.1 Production Costs. On average, the CCC rotation had the greatest average cost of production (Table 1-2). The second and third years of the CCC rotation were corn following corn, resulting in an average fertilizer cost that was \$126 to \$341 ha^{-1} greater for the CCC rotation compared to the other rotations (Figure 1-1). The CCC rotation also had the greatest average seed cost among crop rotations. The AAC rotation had the lowest average production costs compared to the other rotations, due primarily to lower overall costs for fertilizer and pesticide (Table 1-2; Figure 1-1). Although per-hectare seed cost for alfalfa was more expensive than that for soybean and wheat, and similar to that for corn, there were no seed costs in the second year of alfalfa production since it was already established. The AAC rotation also had reduced fertilizer costs because no N fertilizer was applied to corn in this rotation beyond the 21 kg N ha^{-1} applied as $(NH_4)_2SO_4$ to supply S. A literature summary by Yost et al. (2014) found that first-year corn following 2 yr of alfalfa that was direct-seeded on medium-textured soils responded to fertilizer N in only 8% of cases. In comparison, they reported that first-year corn following 1 yr of direct-seeded alfalfa on medium-textured soils, as was the case in the third year of the SAC rotation, responded to fertilizer N in 56% of cases. In this study, first-year corn following 1 yr of alfalfa and corn following soybean both received 135 kg N ha^{-1}.

Pesticide cost was substantially less for the AAC rotation compared to the other crop rotations (Figure 1-1). This was largely because no pesticides were required for second-year alfalfa in the AAC rotation since no insect pests or weeds reached levels warranting treatment. The lack of hand weeding or herbicide requirements to control herbicide-resistant giant ragweed in second-year alfalfa is noteworthy, since corn and soybean plots in all rotations required hand weeding in most years to control giant ragweed (populations as dense as 416 plants m^{-2}) and maintain a zero weed threshold, one of the requirements for the giant ragweed emergence component of this study (Goplen et al., 2016b). Even with dense populations of giant ragweed, no hand weeding was required in wheat or alfalfa plots because herbicide-resistant giant ragweed was successfully controlled with herbicides, increased crop competition, and multiple alfalfa harvests. The cost of weed control likely would have been substantially greater than reported in this study if herbicide-resistant giant ragweed densities of this magnitude were not hand weeded, since the cost of hand weeding was not included in this analysis. Therefore, herbicide cost in this study for rotations that lacked wheat or alfalfa would have been greater if this study fully accounted for the increase in herbicide costs that typically occurs with the presence of herbicide-resistant weeds (Mueller et al., 2005; Norsworthy et al., 2012).

1.4.2 Crop Yields. Average crop yields during the study period were within 28% of the county average of 11.46, 3.49, 2.92, and 6.50 Mg ha^{-1} yr^{-1} for corn, soybean, wheat, and alfalfa, respectively (USDA-National Agricultural Statistics Service, 2016). Soybean yield was 23% less than the county average during the study period (Table 1-3) and likely was associated with soybean sudden death syndrome (*Fusarium virguliforme* L.) confirmed during several years of this study. Soybean sudden death syndrome has the potential to reduce soybean yield up to 100%, though 5 to 15% yield loss is more common (Rupe and Hartman, 1999). Alfalfa yield in this study was greater than the county average during the study period, but varied substantially depending on whether the stand was newly seeded or previously established. Above-average alfalfa yield in this study may have been related to the direct-chopping harvest method that was used, which has lower harvest losses compared to cutting and in-field curing and baling commonly used by farmers (Undersander et al., 2011).

Corn yield in the third rotation-year was greatest with the CSC, SWC, and SAC rotations, although corn yield in the third year with the CSC rotation did not differ from that of CCC and SCC rotations (Table 1-3). Greater corn yield following soybean, wheat, and alfalfa substantiates previous research that has found greater yield when corn is planted following crops other than corn (Edwards et al., 1988; Stanger and Lauer, 2008). Corn yield in the third rotation-year was least with the AAC, SCC, and CCC rotations (Table 1-3). Corn yield in the AAC rotation was less than that in the third year of the CSC, SWC, and SAC rotations, possibly because no additional N fertilizer was applied. No N fertilizer was applied to corn in the AAC rotation since corn following 2 yr of alfalfa that was direct-seeded on medium-textured soils responded to fertilizer N in just 8% of cases (Yost et al., 2014). Corn yield in the third rotation-year was greatest for the SAC, SWC, and CSC rotations (Table 1-3). Greater corn yield in the third rotation-year for the SAC and SWC rotations compared with the SCC and CCC rotations may be due to a "non-N-rotational effect," since corn yield typically is greater when following a crop other than corn (Crookston et al., 1991; Stanger and Lauer, 2008).

1.4.3 Net Return. Net return was calculated using average input costs (Table 1-2) during the study period, average crop yields (Table 1-3), and average crop prices received in Minnesota from 2012 to 2015 (Table 1-1). The CCC rotation was the only rotation which averaged a net positive return in each rotation-year (Table 1-4). Negative net return occurred in rotation-years with soybean, wheat, and first-year alfalfa in the AAC rotation. Greatest average net return for a given rotation-year occurred with second-year alfalfa in the AAC rotation. The large average net return of second-year alfalfa partially contributed to the AAC rotation having the greatest average net return during the study period. Additionally, the N fertilizer replacement value of 168 kg N ha^{-1} credited to corn following 2 yr of alfalfa reduced N fertilizer costs and contributed to greater net return for corn in the AAC rotation compared to corn in other rotations. There was more variation in net return among years for the AAC rotation compared to the other rotations, largely due to the negative net return in first-year alfalfa in this rotation. When net return was averaged across the first and second years of alfalfa in the AAC rotation, as is typically done to evaluate net return from alfalfa, net return was $1765 ha^{-1} yr^{-1}, which was substantially greater than any single-year net return in the other rotations.

To evaluate the full distribution of net returns possible for each crop rotation, both FSD and SDS analyses were performed to determine the stochastically dominant rotations. The CSC, SAC, and AAC rotations were among the dominant rotations based on FSD, as the CSC and SAC rotations dominated the SWC rotation and the AAC rotation dominated the SCC, SWC, and SAC rotations (Table 1-5). This demonstrated that the AAC rotation was the most dominant by FSD and aligns with the AAC rotation having the greatest average net return ($919 ha^{-1} yr^{-1}). The SWC rotation was dominated by the CSC, SAC, and AAC rotations by FSD due to the lower CDF of net returns at all levels of net return, in agreement with the lower average net return for the SWC rotation ($11 ha^{-1} yr^{-1}) compared to the other rotations ($170-$919 ha^{-1} yr^{-1}) (Figure 1-2; Table 1-4).

Using SSD, crop rotations were identified that would be most attractive to decision makers who prefer greater to lesser net return and are risk averse. The CCC, CSC, SAC, and AAC rotations were the stochastically dominant rotations based on SSD (Table 1-5). The AAC rotation dominated all other rotations based on SSD, having greater net returns with less variability, representative of lower financial risk. The AAC rotation had greater net return at lower values of cumulative probability and never produced a negative net return; at greater values of cumulative probability net returns did not differ among the AAC, CSC, and CCC rotations (Figure 1-2). Although the CCC and CSC rotations did occasionally produce greater net return than the AAC rotation, the AAC rotation had less variability; area under the CDF for the

AAC rotation was less than that for the CSC and CCC rotations at all levels of net return, demonstrating that the AAC rotation dominated the CSC and CCC rotations by SSD. First- and second-degree stochastic dominance for the AAC rotation likely was associated with less variable prices for alfalfa during 2012 to 2015 compared to corn, soybean, and wheat (Table 1-1). Above-average and high-quality alfalfa yield, combined with relatively stable alfalfa prices during the study period, resulted in the AAC rotation dominating all other crop rotations by SSD. Adequate and high-quality alfalfa yield in the SAC also contributed to the SAC rotation dominating all other rotations except the AAC rotation by SSD. Although a single year of alfalfa in crop rotations is uncommon, results from this study show that it can provide substantial net return if high yields can be achieved. Adding an additional year of alfalfa to the SAC and AAC rotations likely would increase net return, as high alfalfa yield can generally be sustained for up to 3 yr without additional establishment expenses (Undersander and Barnett, 2008). Previous research has shown that rotations of corn and soybean tend to dominate continuous corn and rotations with wheat or alfalfa by FSD and SSD (Zacharias and Grube, 1984; Stanger et al., 2008); however, the stochastically dominant crop rotations will vary depending on specific scenarios (DeVuyst and Halvorson, 2004). Overall, more diverse crop rotations generally reduce risk through more stable and greater yields and price diversification, where low prices for one crop can be offset by greater prices for another crop in a given year (Helmers et al., 2001; Meyer-Aurich et al. 2006).

Since farmers often adjust the crop planted based on changing market and weather conditions, stochastic dominance analysis was performed for individual crops planted regardless of preceding crop or crop rotation. Net return to corn production was highly variable in this study, ranging from less than -\$300 ha^{-1} yr^{-1} to more than

\$2000 ha^{-1} yr^{-1} (Figure 1-3). Large variation in net return to corn production was largely due to variation in corn price (Table 1-1), as well as variation in input costs among rotations. Due to the large variation in net return for corn, corn dominated soybean and wheat by FSD and SSD but not 1 or 2 yr of alfalfa (Table 1-6). Even with wheat straw harvested to supplement income from grain, corn, soybean, and 1 and 2 yr of alfalfa dominated wheat by FSD and SSD since wheat rarely produced a positive net return. Two years of alfalfa dominated soybean and wheat by FSD, and dominated all crops by SSD since the area under the CDF was less than that for other crops at all levels of net return (Figure 1-3; Table 1-6). One year of alfalfa dominated soybean and wheat by FSD, and dominated all crops except 2 yr of alfalfa by SSD. Stochastic dominance of 1 and 2 yr of alfalfa over all other crops was related to relatively stable alfalfa price and above-average yield, which provided greater net return with less variability. Soybean dominated only wheat by FSD and SSD, likely because soybean yield averaged 23% less than the county average during this study.

1.4.4 Herbicide-Resistant Giant Ragweed Implications. Results from this study indicate that crop rotations that include alfalfa are among the most attractive for financially risk-averse decision makers, confirming that alfalfa is a suitable crop to plant when herbicide-resistant giant ragweed is present. In these same experiments, the AAC rotation was the best rotation for controlling herbicide-resistant giant ragweed, as it had similar levels of seed bank depletion with less total emergence of giant ragweed compared to the other rotations (Goplen et al., 2016b). With reduced emergence of giant ragweed in the AAC rotation, there was less reliance on herbicides since the second year of alfalfa did not require herbicide applications.

The value of the AAC rotation likely would be amplified if the rotation-years with corn and soybean accounted for the hand-weeding required in most years to prevent giant ragweed seed production. No weed escapes occurred in alfalfa or wheat in this study since alfalfa harvests controlled herbicide-resistant giant ragweed in alfalfa and the herbicides used in wheat were effective at controlling giant ragweed. Hand weeding escaped giant ragweed in corn and soybean can substantially increase production costs. Hand weeding glyphosate-resistant palmer amaranth (*Amaranthus palmeri* L.) in Georgia cotton cost \$27 ha^{-1} (Sosnoskie and Culpepper, 2014). If the cost of hand weeding giant ragweed is similar to that for hand weeding palmer amaranth, planting wheat or alfalfa would become much more economical than found in this study since hand weeding was not required for these crops. If giant ragweed is allowed to compete with corn and soybean, corn yield can be reduced by up to 90% with 1.4 giant ragweed plants m^{-2} (Harrison et al., 2001) and soybean yield can be reduced by 45 to 77% with 1.0 giant ragweed plant m^{-2} (Webster et al., 1994).

An additional option for improving control of herbicide-resistant giant ragweed is delayed planting. On average, 90% of giant ragweed in these experiments emerged before June 4 (Goplen et al., 2016b). A single pass with a field cultivator just prior to corn and soybean planting on June 4 has the potential to provide 90% control of giant ragweed (Goplen et al., 2016b). Delayed planting also allows preemergence herbicides to extend residual activity later into the growing season. Due to an abnormally wet spring, corn and soybean planting in 2013 was delayed until June 12, which allowed most giant ragweed to be controlled prior to planting, enabling the postemergence herbicides to be more effective and eliminating the need for hand weeding. Although delayed planting can improve control of giant ragweed in corn and soybean, delaying planting until late May can reduce corn and soybean grain yield by 15 and 10%, respectively (Van Roekel and Coulter, 2011; De Bruin and Pedersen, 2008). If herbicide-resistant giant ragweed is not adequately controlled in corn or soybean, the AAC rotation in this study would be more attractive to risk-averse decision makers.

1.4.5 Conclusions. Results from this study indicate that the AAC rotation would be preferred by financially risk-averse decision makers, especially when herbicide-resistant giant ragweed is present as hand weeding was not required to prevent giant ragweed seed production in alfalfa. This analysis assumed that there is an accessible and established alfalfa market but results likely will differ based on market access. Prices for alfalfa during this study were more stable compared to those for corn, soybean, and wheat. Changes in net return for the AAC rotation based on market access would likely be related to additional costs required to transport alfalfa to an established market. If alfalfa is not a feasible crop for a producer, then the CSC and CCC rotations would be the next most preferable rotations after the AAC rotation, both of which are suitable for herbicide-resistant giant ragweed management. When weed seed production is eliminated, 98% of the giant ragweed seed bank was depleted in 2 yr with all crop rotations in the experiments utilized in this study. Since herbicides with greater efficacy on herbicide-resistant giant ragweed are available for corn compared to soybean, there is potential for the giant ragweed seed bank to be substantially depleted in the 2 yr of corn before planting soybean in the SCC rotation. Therefore, if weed seed production can be prevented for 2 yr during a SCC rotation, the giant ragweed population likely would be depleted enough so that control of giant ragweed control in soybean would be more manageable. This research provides valuable knowledge on the economic performance of crop and crop rotation options for fields in the Midwestern United States with herbicide-resistant giant ragweed. In particular, results from this study demonstrate that alfalfa is a valuable crop in terms of economic net return and management of herbicide-resistant weeds.

Table 1-1. Average prices of alfalfa, corn, soybean, wheat, and wheat straw received in Minnesota from 2012 to 2015.†

Crop	2012	2013	2014	2015	CV‡
	U.S. $ Mg^{-1}				
Alfalfa	246	307	281	218	0.15
Corn	263	169	141	134	0.34
Soybean	525	474	366	316	0.23
Wheat	299	245	201	175	0.24
Wheat straw	80	83	119	91	0.19

† Source: USDA-National Agricultural Statistics Service (2016). Alfalfa and wheat straw prices obtained from Szafranski and Martens (2016).
‡ CV, coefficient of variation.

Table 1-2. Production costs for each crop rotation by rotation-year and across rotation-years.

Rotation-year	Crop rotation†					
	CCC	SCC	CSC	SWC	SAC	AAC
	U.S. $ ha^{-1}$					
1	1875	1341	1875	1341	1341	1446
2	1966	1875	1341	1399	1543	1195
3	1966	1966	1875	1966	1875	1643
Mean	1936	1727	1697	1569	1586	1428

† AAC, alfalfa-alfalfa-corn; CCC, continuous corn; CSC, corn-soybean-corn; SAC, soybean-alfalfa-corn; SCC, soybean-corn-corn; SWC, soybean-wheat-corn.

Table 1-3. Crop yield by rotation-year for each crop rotation.†

Rotation-year	Crop rotation‡					
	CCC	SCC	CSC	SWC	SAC	AAC
	Mg ha^{-1}					
1	12.44	2.82	12.40	2.82	2.67	2.92
2	11.54	12.41	3.07	3.31§	8.66	15.38
3	13.09bc¶	13.09bc	13.51ab	13.79a	13.92a	12.61c

† Grain yield at 155, 130, and 135 g kg^{-1} moisture content for corn, soybean, and wheat, respectively. Alfalfa yield reported as annual total forage dry matter yield.

‡ AAC, alfalfa-alfalfa-corn; CCC, continuous corn; CSC, corn-soybean-corn; SAC, soybean-alfalfa-corn; SCC, soybean-corn-corn; SWC, soybean-wheat-corn.

§Wheat straw yield averaged 3.83 Mg ha^{-1}.

¶ Means for corn grain yield in the third rotation-year followed by the same letter are not significantly different according to Fisher's protected LSD test ($P \leq 0.05$).

Table 1-4. Net return for each crop rotation by rotation-year and across rotation-years.

Rotation-year	Crop rotation†					
	CCC	SCC	CSC	SWC	SAC	AAC
	U.S. \$ ha^{-1}					
1	323.32	-153.80	315.44	-157.56	-217.14	-678.39
2	72.99	317.63	-52.69	-279.89	736.14	2851.44
3	345.41	346.32	511.95	469.79	584.03	584.70
Mean	247.24a§	170.05b	258.23a	10.78c	367.68d	919.25e
SE‡	71.19	63.23	66.74	57.86	67.86	158.53

† AAC, alfalfa-alfalfa-corn; CCC, continuous corn; CSC, corn-soybean-corn; SAC, soybean-alfalfa-corn; SCC, soybean-corn-corn; SWC, soybean-wheat-corn.

§ Means for corn grain yield in the third rotation-year followed by the same letter are not significantly different according to Fisher's protected LSD test ($P \leq 0.05$).

‡ SE, standard error

Table 1-5. Results of first and second degree stochastic dominance analysis of net return for crop rotations.

Crop rotation†	First degree			Second degree		
	Dominates	Indifferent	Dominated by	Dominates	Indifferent	Dominated by
1-CCC	–	2,3,4,5,6	–	4	2,3	5,6
2-SCC	–	1,3,4,5	6	–	1,4	3,5,6
3-CSC	4	1,2,5,6	–	2,4	1	5,6
4-SWC	–	1,2	3,5,6	–	2	1,3,5,6
5-SAC	4	1,2,3	6	1,2,3,4	–	6
6-AAC	2,4,5	1,3	–	1,2,3,4,5	–	–

† 1-CCC, continuous corn; 2-SCC, soybean-corn-corn; 3-CSC, corn-soybean-corn; 4-SWC, soybean-wheat-corn; 5-SAC, soybean-alfalfa-corn; 6-AAC, alfalfa-alfalfa-corn.

Table 1-6. Results of first and second degree stochastic dominance analysis of net return for individual crops, regardless of crop rotation or rotation-year. Net return of 2 yr of alfalfa was calculated as the average of both years.

	First order			Second order		
Crop†	Dominates	Indifferent	Dominated by	Dominates	Indifferent	Dominated by
Corn	S,W	A1,A2	–	S,W	A2	A1
Soybean	W	–	C,A1,A2	W	A1	C,A2
Wheat	–	–	C,S,A1,A2	–	A1	C,S,A2
Annual alfalfa	S,W	C,A2	–	C,S,W	–	A2
2 yr of alfalfa	S,W	C,A1	–	C,S,W,A1	–	–

† A1, Annual alfalfa; A2, 2 yr of alfalfa; C, corn; S, soybean; W, wheat.

Figure 1-1. Average annual production cost by category for each crop rotation. The machinery category includes all costs related to field work, including implement usage, drying, storage, and hauling costs associated with crop production. AAC, alfalfa-alfalfa-corn; CCC, continuous corn; CSC, corn-soybean-corn; SAC, soybean-alfalfa-corn; SCC, soybean-corn-corn; SWC, soybean-wheat-corn.

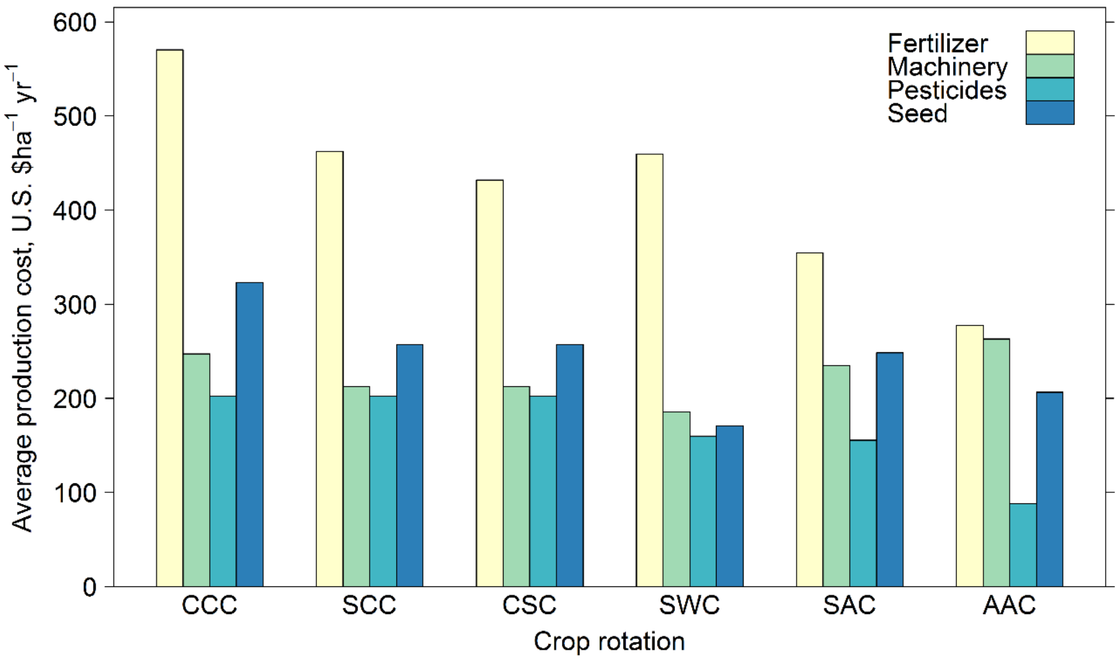


Figure 1-2. Cumulative distribution function of net return by crop rotation. AAC, alfalfa-alfalfa-corn; CCC, continuous corn; CSC, corn-soybean-corn; SAC, soybean-alfalfa-corn; SCC, soybean-corn-corn; SWC, soybean-wheat-corn.

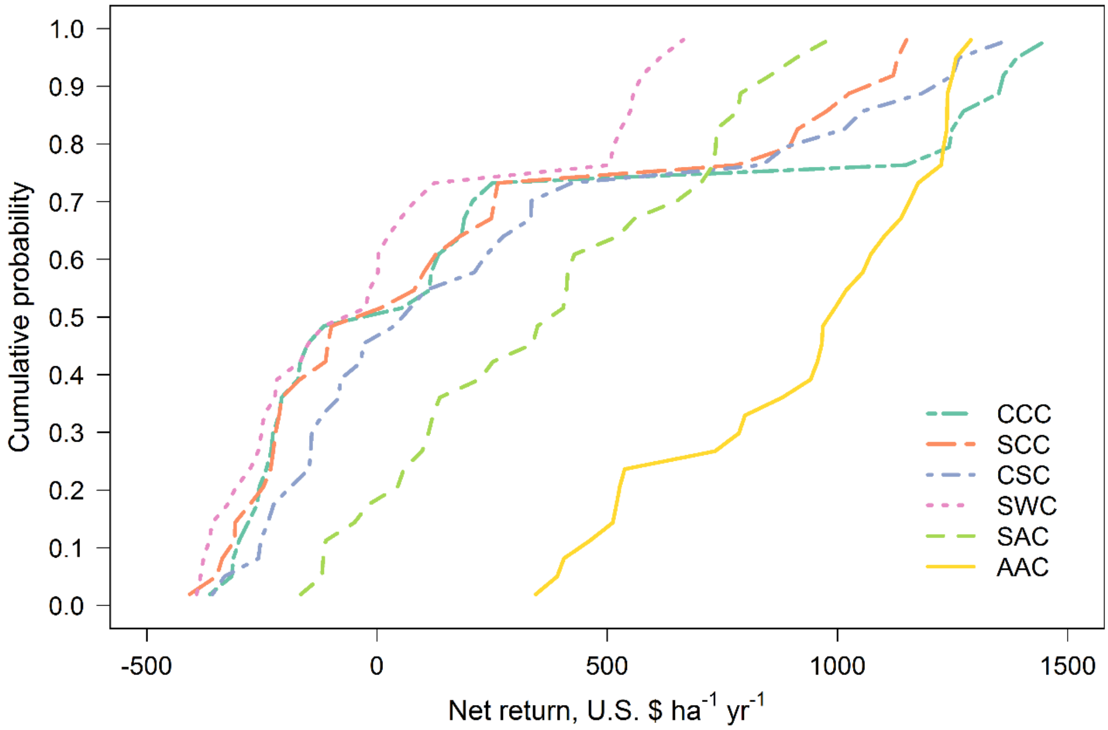
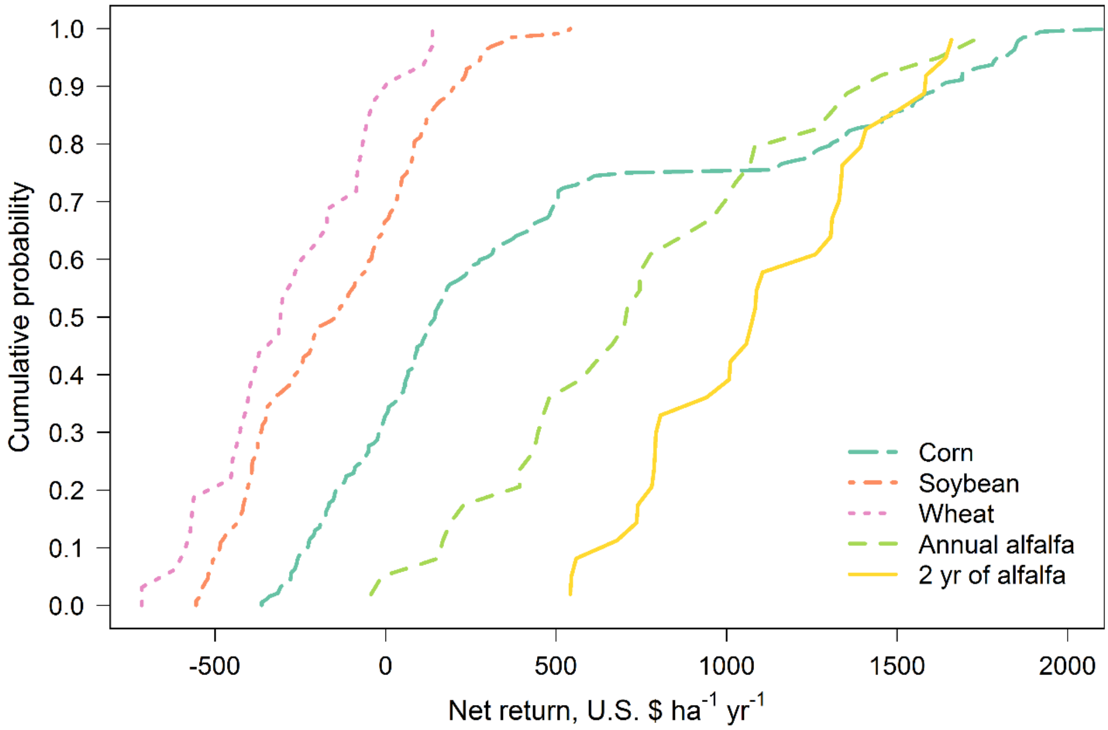


Figure 1-3. Cumulative distribution function of net return by individual crop, regardless of crop rotation or rotation-year. Net return of 2 yr of alfalfa was calculated as the average of both years.



CHAPTER 2: GIANT RAGWEED (*AMBROSIA TRIFIDA*) EMERGENCE MODEL PERFORMANCE EVALUATED IN DIVERSE CROPPING SYSTEMS

2.1 Summary. Accurate weed emergence models are valuable tools for scheduling planting, cultivation and herbicide applications. Multiple models predicting giant ragweed emergence have been developed, but none have been validated in diverse cropping systems. Different crop management practices influence the soil environment, thereby affecting giant ragweed emergence and emergence model performance. This study evaluated the performance of published giant ragweed emergence models across various crop rotations and spring tillage dates in southern Minnesota. Across experiments, the most-robust model was a mixed-effects model predicting emergence in relation to hydrothermal time accumulation with a base temperature of 4.4 C, a base soil matric potential of -2.5 MPa, and a single random effect determined by overwinter growing degree days (GDD) (10 C). The deviations in emergence between individual plots and the fixed-effects model were distinguished by the association between the lower horizontal asymptote (Drop) and maximum daily soil temperature during seedling recruitment. This finding indicates that crops and crop management practices that promote greater maximum daily soil temperature during seedling recruitment will have a shortened lag phase at the start of giant ragweed emergence compared to those with lower soil temperature. This research provides a valuable assessment of published giant ragweed emergence models and illustrates that accurate emergence models can be used to time field operations and improve giant ragweed control across diverse cropping systems.

2.2 Introduction. Planting date, cultivation schedules, and herbicide application timing can improve weed control by being scheduled when weeds are most vulnerable (Menalled and Schonbeck 2011). For example, spring pre-plant tillage or POST herbicide applications are more efficient when the number of weeds emerged is maximized but weed size is small. If tillage or herbicide is applied too early, only a small percentage of weeds will have emerged, whereas if they occur too late weeds may be too large to be vulnerable (Carey and Kells 1995; Gunsolus 1990). Accurate weed emergence models provide a tool to optimize the timing of field operations to obtain maximum weed control (Anderson 1994; Forcella et al. 1993). Weed emergence models can also improve our understanding of abiotic factors influencing seed biology and dormancy release. For example, emergence modeling studies have provided evidence that giant ragweed seed dormancy is related to cold, moist conditions during the overwinter period, supporting previous research (Davis et al. 2013; Schutte et al. 2012).

Giant ragweed is one of the most competitive agricultural weeds in Midwestern United States row-crop production and has developed resistance to glyphosate and acetolactate synthase (ALS) inhibitor herbicides (Heap 2016; Webster et al. 1994). With limited herbicide options effective on giant ragweed, proper herbicide application timing is critical for weed control with herbicides (Buhler et al. 1997). It is equally important to time mechanical weed control such as spring tillage to maximize its effectiveness on early-emerging weeds. Giant ragweed has historically been one of the earliest emerging agricultural weeds in the Midwestern United States, often exhibiting a single early-season flush of emergence (Buhler et al. 1997; Werle et al. 2014), although some populations have developed a delayed emergence pattern (Schutte et al. 2008). Utilizing tillage to control early-emerging weeds not only reduces the reliance on herbicides, but also reduces weed population densities and allows POST herbicide applications to be made to smaller weeds, making them more effective (Sellers et al. 2009).

There are four publications predicting the timing of giant ragweed emergence based on concurrent weather and soil characteristics (Archer et al. 2006; Davis et al. 2013; Schutte et al. 2008; Werle et al. 2014). All models base predictions on thermal time accumulation [either growing degree days (GDD) or hydrothermal time (HTT)], but utilize different soil temperature and moisture criteria for thermal time accumulation (Table 2-1). All models have used the Soil Temperature and Moisture Model (STM^2) (Spokas and Forcella 2009) to predict soil temperature and moisture using site-specific soil information and daily precipitation as well as minimum and maximum air temperature from a nearby weather station. Although the STM^2 model can be highly accurate, it does not account for soil shading as crop canopies develop (Perreault et al. 2013; Schutte et al. 2008).

Archer et al. (2006) published the first emergence model for giant ragweed based on several experiments conducted at field sites ranging from Ohio to Colorado and Missouri to Minnesota. Another giant ragweed emergence model developed by Schutte et al. (2008), based on research in Ohio, provides emergence predictions for giant ragweed that express a biphasic emergence pattern. Models developed by Davis et al. (2013) were constructed using emergence data from multiple giant ragweed seed accessions and 18 site-years of data from locations throughout the United States Corn Belt. An additional giant ragweed emergence model was developed by Werle et al. (2014) from several site-years of data collected in Iowa. None of these giant ragweed emergence models have been evaluated in differing crop management practices.

Davis et al. (2013) and Schutte et al. (2008) developed giant ragweed emergence models by evaluating giant ragweed emergence with no surrounding vegetation, while

Werle et al. (2014) developed emergence models in an experiment planted to soybean that achieved a crop canopy after the majority of giant ragweed emergence had occurred. Although Schutte et al. (2008) validated their model in both no-tillage and tilled conditions, the type of crop, crop residue, and tillage influences the soil environment which can alter giant ragweed emergence. Since all published emergence models were constructed in either fallow or annual row-crop systems, it is likely that model performance, or how closely a model predicts actual giant ragweed emergence, will decrease in perennial crops or crops planted early in the season and in narrow rows since they affect early-season soil temperature and moisture (Liebman and Dyck 1993). Giant ragweed emergence has been shown to be prolonged with less total seedling recruitment in established alfalfa, which was attributed to lower soil temperatures being less conducive to giant ragweed recruitment (Goplen et al. 2016b; Wortman et al. 2012). It is important to validate the applicability of giant ragweed emergence models in diverse cropping systems to identify reliable models for timing field operations. The objectives of this research were to evaluate the performance of published giant ragweed emergence models across contrasting cropping systems, and determine biotic or abiotic factors associated with deviations in emergence model predictions.

2.3 Materials and Methods

2.3.1 Description of Models. Eleven models derived from four publications were included in this analysis (Table 2-1). All models were based on soil conditions predicted by STM^2, despite using predictions from different soil depths (Spokas and Forcella 2009) (Table 2-1). The single fixed-effect model from Archer et al. (2006) predicts giant ragweed emergence with HTT using the Gompertz function:

$$Y = 100 * \exp[-6 * \exp(-0.02*\mathrm{HTT})] \qquad [1]$$

where Y is cumulative percent emergence and HTT is the predictor variable. All other models utilize the Weibull function to predict giant ragweed emergence. The models from Schutte et al. (2008) and Werle et al. (2014) include only fixed effects:

$$Y = M * \{1 - \exp [(-\exp (\mathrm{lrc})) * (\mathrm{GDD\ or\ HTT} - z) \wedge c]\} \qquad [2]$$

where Y is cumulative percent emergence, M is the upper horizontal asymptote, lrc is the natural log of the rate of increase, GDD or HTT is the predictor variable, z is the time of first emergence, and c is the curve shape parameter. The fixed-effects models have model parameters that are fixed across all locations, years, and changing weather conditions, with model parameters presented in Table 2-1. Davis et al. (2013) included an additional fixed effect for a lower horizontal asymptote (Drop) to the Weibull function as in Equation 3:

$$Y = M – (\mathrm{Drop} + drop) * \exp [(-\exp (\mathrm{lrc} + lrc)) * (\mathrm{HTT}) \wedge c] \qquad [3]$$

as well as random effects for *drop* and *lrc* which were determined by their published associations with weather variables and were different for each site-year (Equation 3). The terms for drop included by Davis et al. (2013) determine how much lower the lower horizontal asymptote is relative to the upper horizontal asymptote, which had a fixed value of 99.8 for all models derived from Davis et al. (2013) (Table 2-1). In Equation 3, Drop and *drop* are the fixed and random effects, respectively, for the lower horizontal asymptote relative to the upper asymptote, and lrc and *lrc* are the fixed and random effects, respectively, for the natural log of the rate of increase. Fixed-effect parameters for all models are presented in Table 2-1, while random-effect parameters were estimated from their associations with weather variables found in Davis et al. (2013).

The model from Schutte et al. (2008) was a two-part model, with a pre- and post-lag phase component based on the Weibull function, designed to predict emergence of giant ragweed with a biphasic emergence pattern. Both phases of this model had a HTT predictor variable, but had different base soil matric potential and model parameters for each phase (Table 2-1). Werle et al. (2014) presented two models, one of which was the best giant ragweed emergence model in their study and another which was a common model among other weed species evaluated in their study. Both models from Werle et al. (2014) were fixed-effects Weibull functions with GDD predictor variables, but with different base temperatures for GDD calculation and different model parameters (Table 2-1).

The models from Davis et al. (2013) were two mixed-effects Weibull functions with a HTT predictor variable. The models from Davis et al. (2013) were for either arable or riparian accessions of giant ragweed and each model had different fixed-effect parameters for lrc and *c*, but the same fixed-effect parameters for *M* and Drop. In addition to the fixed effects, these models included random effects for *lrc* and *drop*. Davis et al. (2013) found that overwinter GDD (10 C) and rainfall during seedling recruitment were both negatively associated with the random effect *lrc*, and that rainfall during seedling recruitment was negatively associated with the random effect d*rop*. Davis et al. (2013) concluded that these weather variables are what influenced deviations from the fixed-effects-only models, and therefore can be used to improve model predictions in years or locations with differing weather conditions. The associations found by Davis et al. (2013) between weather variables and random effects for *lrc* and *drop* were used to predict the random-effect parameters for each site-year of this study, which is how models 4 to 8 were derived in Table 2-2. All giant ragweed populations in our study were from arable accessions, so arable accession model 2 was used as a basis for the mixed-effects models 4 to 8 (Tables 2-1, 2-2). Models 4 to 8 had the same fixed effects as arable accession model 2, but had different random effects for each site-year that were predicted from Davis et al. (2013).

2.3.2 Crop Rotation Experiment. Two field experiments were initiated in 2012 and 2013 at separate sites with giant ragweed resistant to glyphosate and ALS-inhibitor herbicides near Rochester, MN (43.91°N, 92.56°W). Crop management details are outlined in Goplen et al. (2016b) and consisted of six three-year crop rotation treatments applied in a randomized complete block design with four replications. Crops in the rotations were corn (*Zea mays* L.), soybean [*Glycine max* L. (Merr.)], wheat (*Triticum aestivum* L.), and alfalfa (*Medicago sativa* L.). Rotations were continuous corn, soybean-corn-corn, corn-soybean-corn, soybean-wheat-corn, soybean-alfalfa-corn, and alfalfa-alfalfa-corn. Giant ragweed emergence was monitored on a weekly basis with emergence data from a total of 120 experimental units over 3 years being used for emergence model analysis, as weekly emergence data was not collected in 2012.

2.3.2 Tillage Experiment. Two additional field experiments were conducted in 2015 near Rochester, MN (43.91°N, 92.56°W) and at the University of Minnesota Rosemount Research and Outreach Center near Rosemount, MN (44.70°N, -93.08°W). Both sites had giant ragweed resistant to glyphosate and at Rochester, MN giant ragweed was also resistant to ALS-inhibitor herbicides. Each experiment had six tillage treatments arranged in a randomized complete block design with four replications. The tillage treatments included multiple dates of spring tillage timed relative to the initiation of giant ragweed emergence. Treatments included tillage with a field cultivator at a depth of 10 cm at emergence onset, at 14, 28, and 42 d after emergence onset, at emergence onset and repeated at 28 d after onset, and no tillage. At Rochester, MN, two replications were in oat stubble that had no fall tillage, and the other two replications were in fall chisel plowed corn stubble. At Rosemount, MN, all replications took place in fall chisel plowed soybean stubble. Plots at Rosemount, MN were 3 by 6 m, and plots at Rochester, MN were 3.7 by 6 m to accommodate equipment size. Ten fixed 0.09-m^2 quadrats were placed in each plot. Giant ragweed emergence was monitored by counting and removing emerged seedlings in each quadrat on a weekly basis, starting at emergence onset and continuing for at least 10 wk or until emergence ceased. All emergence data were converted to a cumulative percentage of giant ragweed that emerged each week. These tillage timing experiments contributed data from 48 experimental units for analysis of giant ragweed emergence models.

2.3.3 Environmental effects. Daily precipitation and minimum and maximum air temperatures were obtained from the National Weather Service station within 5 km of each study location. Weather data from each weather station was used to predict daily soil temperature (C) and moisture (MPa) at 1, 2 and 5-cm depths using STM^2 (Spokas and Forcella 2009). The STM^2 predictions were based on daily maximum and minimum air temperature, daily precipitation, soil properties (sand, silt, clay, and organic matter), latitude, longitude, and elevation.

Thermal time for each giant ragweed emergence model was calculated using the method specified in the respective publication. All emergence models calculated GDD as:

$$\text{GDD} = \sum_{S1}^{S2} \frac{(T_{max} + T_{min})}{2} - T_b \qquad [4]$$

where $T_{\max}$ is maximum daily soil temperature, $T_{\min}$ is minimum daily soil temperature, T_b is base temperature for GDD calculation presented in Table 2-1, and

S_1 and S_2 are beginning and ending dates for the specific model, respectively. For models using hydrothermal time (HTT) to predict emergence, HTT was calculated as:

$$\text{HTT} = \sum_{\text{S1}}^{\text{S2}} \theta_H \, GDD \qquad [5]$$

where GDD were calculated according to Equation 4, θ_H = 1 when soil matric potential was in the model's designated interval, and θ_H = 0 when soil matric potential was not in the model's designated interval (Table 2-1). Therefore, thermal time was only accumulated when soil moisture was in the designated interval. Soil temperature at the 5-cm depth was recorded hourly in all plots from all experiments using temperature sensors (Hobo Water Temp Pro v2, Pocasset, MA). Soil temperature data from temperature sensors was used to explore deviations from emergence predictions in crop rotation and tillage timing treatments.

2.3.4 Statistical Analysis. Measures of model performance in our study were based on comparison between observed and predicted values for cumulative percent emergence of giant ragweed across the entire seedling recruitment period. Corrected Akaike's information criterion (AICc) was used to evaluate competing giant ragweed emergence models across experiments. This criterion includes a correction for sample size and is recommended in practice over traditional AIC (Anderson 2008; Hurvich and Tsai 1989; Sugiura 1978). It is based on the minimization of maximum likelihood criterion and is calculated as:

$$\text{AICc} = -2\log\left(\mathcal{L}\left(\hat{\theta}\right)\middle|x\right) + \frac{2K(K+1)}{n-K-1} \qquad [6]$$

where the first term involves the log-likelihood of the model, given the data, while the second term penalizes a model for *K* additional parameters and sample size of *n*. Models with lower values of AICc indicate they better-represent reality given the data. Akaike weights (w_i) were calculated from the AICcs for the 11 models to determine the probability that a given model is the best descriptor of reality among the candidate models. Akaike weights (w_i) were calculated as:

$$w_i = \frac{e^{-1/2\Delta_i}}{\sum_{r=1}^{R} e^{-1/2\Delta_r}} \qquad [7]$$

where Δ_i is the AICc difference between the top model and the *i*th alternative, and R is the number of candidate models (Anderson 2008; Burnham and Anderson 2002; Hoeting et al. 1999). Akaike weights (w_i) closer to 1 indicate stronger support for a candidate model given the data. This methodology has been used in previous giant ragweed emergence modeling studies to select the best-fitting predictive model while minimizing the number of parameters included (Davis et al. 2013; Werle et al. 2014).

Since AICc will rank models even if none perform well, it is recommended to use additional performance criteria (Anderson 2008; Kobayashi and Salam 2000; Legates and McCabe 1999; Meek et al. 2009; Tedeschi 2006). Following earlier methods (Schutte et al. 2008; Werle et al. 2014), goodness-of-fit for each model was analyzed using root mean square error (RMSE) and the concordance correlation coefficient (*CCC*) to provide measures of giant ragweed emergence model precision and accuracy. One of the most reliable estimates of model prediction accuracy is RMSE, and is recommended when using AICc model selection methods (Anderson 2008; Legates and McCabe 1999; Tedeschi 2006). The RMSE is calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \qquad [8]$$

where O_i and P_i are the observed and predicted values of the cumulative percentage of giant ragweed emerged, respectfully, and n is the number of comparisons. The *CCC* was calculated as an additional model performance measure since it provides a measure of precision and accuracy, whereas RMSE only provides an estimate of model accuracy (Mitchell 1997). The *CCC* is:

$$CCC = rA \qquad [9]$$

which is the product of Pearson's correlation coefficient (*r*) and accuracy (*A*). Accuracy (*A*) is a bias correction factor calculated as:

$$A = \frac{4s_x s_y - r(s_y^2 + s_x^2)}{(2-r)\left(s_y^2 + s_x^2\right) + (\mu_y - \mu_x)^2} \qquad [10]$$

where s_x is mean deviation *x* from μ_x, s_y is mean deviation *y* from μ_y, μ_y is the mean of the observed values, and μ_x is the mean of the model prediction. The *CCC* can range from -1 to 1, with values near 1 indicating better fitting models (Meek et al. 2009).

Deviations from the best giant ragweed emergence model were analyzed to determine if they were associated with crop rotation or tillage treatments, or with specific soil temperature conditions. Since the best giant ragweed emergence model was from a mixed-effects model, random effects were fit to the observed data using maximum likelihood methods in each treatment and site-year as done by Davis et al. (2013). Regression analyses were then performed to determine the relationship between fitted random effects, which were the dependent variables, and crop rotation and tillage treatments, as well as observed soil temperature data. All analyses were performed using R version 3.1.3 (R Foundation for Statistical Computing, Wien, Austria).

2.4 Results and Discussion

2.4.1 Giant Ragweed Emergence. Giant ragweed emerged early in the growing season in all experiments, where on average 90% of giant ragweed emergence occurred on May 29 and June 4 in the tillage and crop rotation experiments, respectively (Goplen et al. 2016b). Crop rotations with annual crops had similar giant ragweed emergence phenology, whereas emergence was slightly prolonged in established alfalfa, likely due to the prominent early-season crop canopy. Tillage treatment reduced giant ragweed emergence the week following tillage, likely because tillage disrupted germinating seedlings and prevented them from emerging the week following tillage. Tillage treatments had similar levels of total giant ragweed emergence ($P = 0.466$), however, indicating that tillage did not stimulate or suppress total giant ragweed emergence.

Across the crop rotation and tillage timing experiments, soil temperature at the 5-cm depth predicted by the STM^2 was associated with observed soil temperature ($R^2 = 0.88$, $P < 0.001$) (Figure 2-1). Although the observed and predicted soil temperatures were associated, the STM^2 had a mean bias of 2.9 C, indicating that the STM^2 predicted soil temperature to be 2.9 C warmer on average than what was observed. This finding is similar to that reported by Perreault et al. (2013), who reported a mean bias of 2.5 C for STM^2 on loamy soils similar to soils at both of our study locations. The mean bias of the STM^2 among crop rotation and tillage timing treatments ranged from 1.7 to 3.9 C. Established alfalfa and wheat had the greatest mean bias values of 3.8 and 3.9 C, respectively, while soybean planted into soybean stubble had the lowest mean bias value of 1.7 C. The STM^2 does not account for changes in crop canopy during the growing season, which likely explains why the STM^2 predictions had a greater bias in established alfalfa and wheat, which were established earlier and in narrower rows compared to corn and soybean.

2.4.2 Model Performance. Across all experiments and site-years, giant ragweed emergence was best fit by model 5, a mixed-effects model derived from the arable accession model of Davis et al. (2013) (Tables 2-1, 2-2). Model 5 had the lowest AICc, greatest Akaike weight (w_i), lowest RMSE, and greatest *CCC* among candidate models, indicating that it had the best fit of emergence across diverse cropping systems in this study (Table 2-2). Model 5 included the fixed effects specified in Table 2-1, and the random effect W *lrc* determined by overwinter GDD (10 C) accumulated from October through March (Table 2-1). The random effect W *lrc* included in model 5 alters the predicted rate of emergence, where greater values indicate more rapid emergence. Davis et al. (2013) found *lrc* to be negatively associated with overwinter GDD (10 C), meaning *lrc* is greater and emergence progresses more rapidly following colder overwinter periods. The more rapid progression of giant ragweed emergence following colder over-winter periods observed in this study has been shown to be related to greater dormancy loss following cold and moist conditions (Ballard et al. 1996; Davis et al. 2013; Schutte et al. 2012). Overwinter GDD (10 C) accumulated in this study ranged from 20 to 67 GDD (10 C), which was comparable to the coldest overwinter periods observed by Davis et al. (2013), which ranged from 0 to 300 GDD (10 C). This resulted in more rapid emergence predictions in all site-years of our study compared to the fixed-effects-only model 2 (Figure 2-2). Compared to model 2, including the random effect *lrc* based on overwinter GDD (10 C) in model 5 improved model performance by reducing RMSE by 0.04 and increasing *CCC* by 0.03 (Figure 2-2; Table 2-2). The improved emergence predictions with model 5 compared to the fixed-effects-only model 2 confirm the findings of Davis et al. (2013) that random effects for *lrc* describe deviations from the fixed-effects-only model 2 (Table 2-2).

Model 8, a mixed-effects model derived from Davis et al. (2013) with fixed effects and two random effects, was the second-best performing giant ragweed emergence model evaluated in this study. The random effects in model 8 included the same random effect for *lrc* (W *lrc*) included in model 5 based on overwinter GDD (10

C), along with an additional random effect for *drop* (P *drop*) which represents the lower horizontal asymptote relative to the upper asymptote. Davis et al. (2013) found an association (r = -0.39, P = 0.10) between *drop* and precipitation accumulated during seedling recruitment, which was used to predict *drop* in model 8 (AS Davis, personal communication). The negative association between *drop* and precipitation during seedling recruitment indicates that smaller values for *drop* occur when there is greater precipitation during seedling recruitment, which results in an extended lag phase when there is greater precipitation during seedling recruitment. Including W *lrc* and P *drop* in model 8 resulted in better model performance than the fixed-effects-only model 2. Model 8 had an Akaike weight (w_i) of <0.001, implying low probability that it was the best among the candidate models, and that it did not predict emergence as well as model 5 (Table 2-2).

Models 4, 6, and 7 were also mixed-effects models derived from Davis et al. (2013) for arable accessions of giant ragweed, but were inferior compared to model 5 (Table 2-2). Model 6 included a single random effect for *drop* determined by precipitation accumulated during seedling recruitment (P *drop*), which resulted in model performance measures only marginally better than the fixed-effects-only model 2 (Table 2-2). Models 4 and 7 had a random effect for *lrc* determined by precipitation during seedling recruitment (P *lrc*), and model 7 included an additional random effect for *drop* based on precipitation accumulated during seedling recruitment (P *drop*). Random effects for *lrc* and *drop* were determined from Davis et al. (2013) by the negative associations between *lrc* and *drop* and precipitation accumulated during seedling recruitment. Among all models derived from Davis et al. (2013), the two best-fitting models across our experiments included a random effect for *lrc* determined by overwinter GDD (models 5 and 8), while the worst-fitting models determined the random effect for *lrc* by precipitation accumulated during seedling recruitment (models 4 and 7). These findings indicate that *lrc* is more closely associated with overwinter GDD (10 C) than precipitation during seedling recruitment (Table 2-2). Random-effect model parameters based on overwinter GDD (10 C) are also easier to use in making real-time emergence predictions, since random effects predicted from overwinter GDD (10 C) are known prior to giant ragweed recruitment. Random-effect parameters based on precipitation during the seedling recruitment period are unknown until the end of seedling recruitment, meaning real-time emergence predictions will require random-effect parameters to be recalculated as precipitation accumulates, or for historical averages and weather forecasts to be utilized in predicting random-effect parameters.

Model 9 was derived from giant ragweed with a biphasic emergence pattern in Ohio (Schutte et al. 2008) and was among the top-performing models in this study. In this study, giant ragweed emergence generally occurred after the early flush but before the late flush of emergence predicted by model 9. This monophasic emergence pattern aligning between the two flushes of emergence predicted by model 9 indicates that giant ragweed in Minnesota have not diverged in their emergence timing as populations found in Ohio (Figure 2-2).

The 2.9 C bias of STM^2 temperature predictions caused predicted thermal time to accumulate faster than what actually occurred, and contributed to premature giant ragweed emergence predictions for models 1, 3, 10, and 11 in all site-years (Figure 2-2). The inaccuracy of STM^2 was likely due to its inability to account for changing canopy cover as crops developed during the growing season (Perreault et al. 2013), since the predictions deviated most from observed soil temperature when alfalfa and wheat were grown. The STM^2 model was likely more accurate in previous giant ragweed emergence modeling studies since they were developed with little or no canopy coverage (Archer et al. 2006; Davis et al. 2013; Schutte et al. 2008; Werle et al. 2014). Including a 2.9 C mean bias correction factor for STM^2 predictions decreased the RMSE of models 1, 3, 10 and 11 by 0.06, 0.03, 0.09, and 0.08, respectfully. However, including the mean bias correction factor increased the RMSE of model 5 by 0.03, indicating that model 5 without a bias correction was still the best among all models evaluated.

2.4.3 Soil temperature associations. The mixed-effects models derived by Davis et al. (2013) provide a versatile framework to study giant ragweed emergence since unexplained model deviations can be attributed to environmental variation (Luschei and Jackson 2005). The associations found by Davis et al. (2013) allowed the derivation of mixed-effects models 4 through 8 in this study. Using this approach, new estimates of the random effects *drop* and *lrc* were determined for the arable accession model (model 2) from Davis et al. (2013) for each site-year and treatment combination in our study. Regression analyses were performed to determine associations between random effects and experimental treatments as well as soil temperature (average daily minimum, maximum, mean, and fluctuation in temperature for various intervals during the seedling recruitment period). Neither crop rotation sequence nor tillage timing treatments were associated with the estimated random effects *drop* or *lrc* (R^2 = 0.07 to 0.42, P = 0.55 to 0.99). There also were no associations between the estimated random effects for *lrc* and soil temperature variables (R^2 = 0.01 to 0.07 to, P = 0.17 to 0.99). All soil temperature variables analyzed were positively associated with the estimated random effects for *drop* (R^2 = 0.24 to 0.72, P < 0.001 to 0.006), meaning warmer soil temperature variables or greater temperature fluctuations had greater fitted random effects for *drop*. The soil temperature variable most strongly associated with the fitted random effect for *drop* was the maximum daily soil temperature during the entire seedling recruitment period (R^2 = 0.72, P < 0.001). This relationship indicates that greater maximum soil temperatures during seedling recruitment were associated with greater fitted random effects for *drop*, the term representing the lower horizontal asymptote of the Weibull function (Figure 2-3). A greater random effect for *drop* equates to a shorter lag period at the start of giant ragweed emergence.

Observed average daily soil temperature fluctuation during the entire seedling recruitment period was the second most-significant association with the estimated random effects for *drop* (R^2 = 0.70, P < 0.001) (Figure 2-3). It is possible that either the amplitude or number of temperature fluctuations influences giant ragweed emergence rather than maximum soil temperature, as shown for other weed species including Johnson grass (*Sorghum halpense* L.) and large crabgrass (*Digitaria sanguinalis* L.) (Benech Arnold et al. 1990a, b; Forcella et al. 2000; King and Oliver 1994). Daily maximum soil temperature was the primary factor influencing daily temperature fluctuation, as evidenced by the strong association between the two variables (r = 0.98, P < 0.001), indicating that greater daily maximum soil temperature is more influential on daily soil temperature fluctuation than daily minimum soil temperature, which has been reported previously (Perreault et al. 2013). These findings indicate that giant ragweed emergence will have a shorter lag phase at the start of emergence in environments with greater maximum daily soil temperature and corresponding greater soil temperature fluctuation. Davis et al. (2013) stated that the associations they found between random effects for *lrc* and precipitation accumulated during seedling recruitment may have been caused by increased cloud cover accompanying increased precipitation. Cloud cover also limits maximum daily soil temperature, and since soil temperature was not directly measured in Davis et al. (2013), it is possible that the association between random effects and precipitation during seedling recruitment was driven by maximum daily soil temperature or daily temperature fluctuation as found in this study.

The positive association between random effects for *drop* and mean maximum daily soil temperature supports the findings of Goplen et al. (2016b), where giant ragweed emergence extended later into the growing season in established alfalfa compared to annual crops. The extended emergence was likely due to lower soil temperatures causing a longer initial lag period in emergence. Longer initial lag periods in emergence could also be expected in other crops established early in the growing season that limit soil temperature, such as small grains or cover crops (Zhang et al. 2009), although this was not shown to be the case for wheat (Goplen et al. 2016b). It is also possible that crop management practices maintaining increased soil residue associated with conservation tillage will have similar effects on giant ragweed emergence since they can also affect soil temperature (Griffith et al. 1973; Kladivko et al. 1986).

2.4.4 Conclusions. Model 5, a mixed-effects model derived from Davis et al. (2013) that included a random effect for *lrc* based on overwinter GDD (10 C), was the model that most accurately predicted giant ragweed emergence across crop rotations and spring tillage dates. The top four models that best-fit giant ragweed emergence in this study originated from Davis et al. (2013), with the top two models including random effects predicted by overwinter GDD (10 C). This is supported by studies of giant ragweed seed dormancy, which found that cold and moist conditions during winter enhances seed dormancy release (Ballard et al. 1996; Schutte et al. 2012).

This is the first study to verify the utility of previously published giant ragweed emergence models under a diversity of crop management practices, and supports previous research showing that giant ragweed emergence is affected by winter weather. This research also suggests that crops such as alfalfa, small grains, and cover crops, which have lower soil temperature during seedling recruitment compared to annual row crops, will have a longer lag phase at the initiation of giant ragweed emergence, potentially extending emergence later into the growing season. As herbicide-resistant giant ragweed continues to be problematic, robust emergence model predictions will be increasingly important to optimize planting, tillage, and herbicide application dates in a variety of crop management systems to improve giant ragweed control.

Table 2-1 Summary of published giant ragweed emergence model parameters.

Citation	Model number	Model details	Prediction variable	GDD base (C)	HTT base (MPa)	Soil data (depth)	Equation type	Weibull model parameters				
								M	*z*	*c*	lrc	Drop
Archer et al. (2006)	1	Fixed	HTT	4.4	-0.15	STM[2] (5cm)	Gompertz	–	–	–	–	–
Davis et al. (2013)	2,4,5,6,7,8[a]	Mixed (arable)	HTT	4.4	-2.5	STM[2] (2cm)	Weibull	99.8	–	2	-12.7[b]	105.7[b]
Davis et al. (2013)	3	Mixed (riparian)	HTT	4.4	-2.5	STM[2] (2 cm)	Weibull	99.8	–	1.38	-6.2[b]	105.7[b]
Schutte et al. (2008)	9	Fixed (prelag)	HTT	2.0	-10	STM[2] (1cm)	Weibull	60	60	1.6	-8.2	–
Schutte et al. (2008)	9	Fixed (postlag)	HTT	2.0	-30	STM[2] (1cm)	Weibull	40	600	1.23	-7.4	–
Werle et al. (2014)	10	Fixed (common)	GDD	9.0	–	STM[2] (2 cm)	Weibull	100	0	1.6573	-7.0	–
Werle et al. (2014)	11	Fixed (best)	GDD	13.0	–	STM[2] (2 cm)	Weibull	100	0	1.2593	-3.5	–

[a] Models include the same fixed effects but different random effects for lrc and/or Drop determined by weather variables

[b] indicates model also includes random effects for the given parameter determined by weather variables

Abbreviations: *c*, curve shape parameter; drop, lower horizontal asymptote relative to upper asymptote; GDD, growing degree days; HTT, hydrothermal time; lrc, natural log of the rate of increase; *M*, upper horizontal asymptote; STM^2, soil temperature and moisture model (Spokas and Forcella 2009); *z*, HTT of first emergence

Table 2-2. Summary of model performance criteria across both experiments and site years.

Model no.	Model	GDD base Temperature (C)	HTT base moisture (MPa)	Random effects	AICc	w_i	RMSE	*r*	*A*	*CCC*
5	Davis arable	4.4	-2.5	W *lrc*	-5383	>0.999	0.18	0.87	0.98	0.85
8	Davis arable	4.4	-2.5	W *lrc* + P *drop*	-5337	<0.001	0.19	0.87	0.96	0.83
6	Davis arable	4.4	-2.5	P *drop*	-4869	<0.001	0.21	0.88	0.94	0.82
2	Davis arable	4.4	-2.5		-4806	<0.001	0.22	0.87	0.94	0.82
9	Schutte	2.0	-10/-30		-4447	<0.001	0.25	0.81	0.63	0.51
7	Davis arable	4.4	-2.5	P *lrc* + P *drop*	-3731	<0.001	0.31	0.76	0.89	0.68
4	Davis arable	4.4	-2.5	P *lrc*	-3566	<0.001	0.32	0.74	0.89	0.66
10	Werle	9.0	–		-2919	<0.001	0.40	0.60	0.18	0.12
11	Werle	13	–		-2706	<0.001	0.43	0.46	0.27	0.13
1	Archer	4.4	-0.15		-2680	<0.001	0.43	0.61	-0.01	-0.01
3	Davis riparian	4.4	-2.5		-2543	<0.001	0.45	0.61	-0.15	-0.09

Abbreviations: *A*, measure of accuracy; AICc, corrected Akaike's Information Criterion; w_i, Akaike weight; *CCC*, concordance correlation coefficient (product of *r* and *A*); GDD, growing degree days; HTT, hydrothermal time; P *drop*, *drop* determined by precipitation during recruitment; P *lrc*, natural log of the rate of increase determined by precipitation during recruitment; *r*, Pearson's correlation coefficient; RMSE, root mean square error; W *lrc*, natural log of the rate of increase determined by winter GDD (10 C) from October to March.

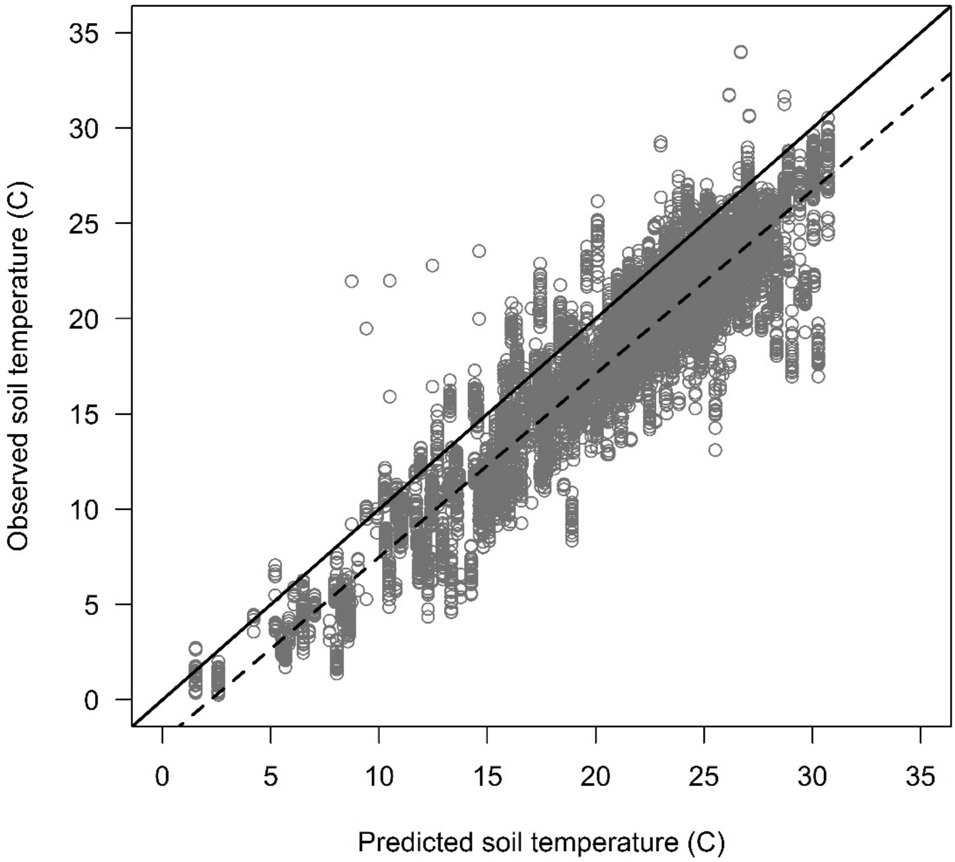


Figure 2-1. Daily average soil temperature at the 5-cm depth predicted by the Soil Temperature and Moisture Model (STM^2) during the crop rotation and tillage timing experiments relative to observed soil temperature. The solid 1:1 line ($y = x$) indicates perfect agreement between observed and predicted soil temperature, while the dotted line indicates the fitted regression equation ($y = 0.96x - 2.1$, $R^2 = 0.88$, $P < 0.001$) between observed and predicted soil temperature.

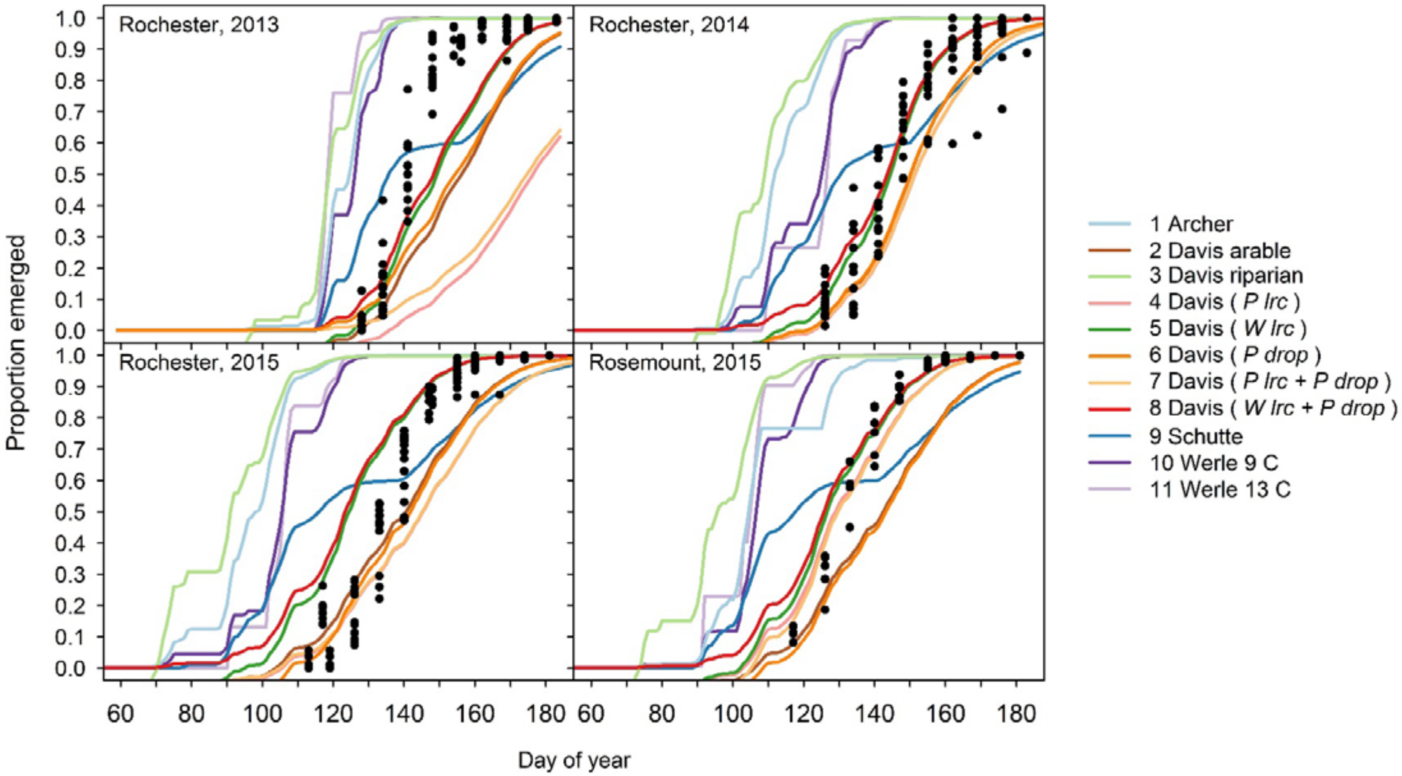


Figure 2-2. Predicted cumulative giant ragweed emergence by model in relation to observed mean cumulative emergence in each experimental treatment. Random effects included in the Davis et al. (2013) arable-accession mixed-effects model are shown in parentheses. Abbreviations: P *drop*, *drop* determined by precipitation during recruitment; P *lrc*, natural log of the rate of increase determined by precipitation during recruitment; W *lrc*, natural log of the rate of increase determined by winter GDD (10 C) accumulated from October to March.

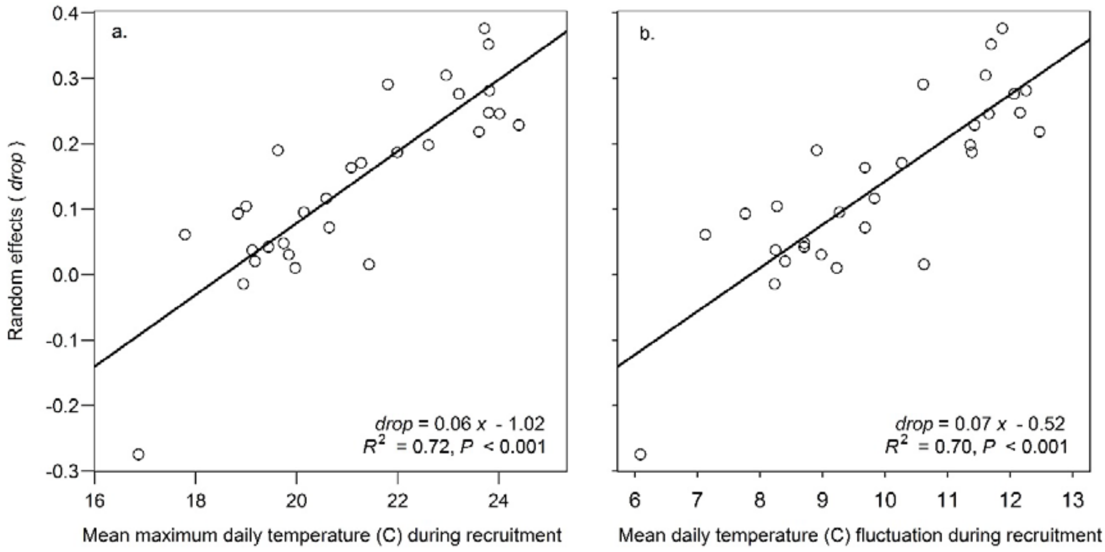


Figure 2-3. Association between the estimated random effects of *drop* and a) mean maximum daily temperature observed at a soil depth of 5 cm during the seedling recruitment period, and b) mean daily temperature fluctuation at a 5-cm soil depth during seedling recruitment.

CHAPTER 3: INFLUENCE OF SPRING TILLAGE ON GIANT RAGWEED EMERGENCE

3.1 Summary. Herbicide-resistant biotypes of giant ragweed are becoming widespread, making control with herbicides increasingly difficult. To improve control of giant ragweed and prevent the proliferation of resistant biotypes, it is necessary to use integrated methods of weed control. Pre-plant tillage is a non-chemical control method for managing herbicide-resistant giant ragweed in annual row-crop production since giant ragweed is one of the earliest emerging weeds plaguing the Midwestern United States. This study evaluated the effect of spring tillage timing on total emergence and emergence patterns of giant ragweed at two locations in Minnesota. Spring tillage treatments utilized a field cultivator with a single pass of tillage at onset of giant ragweed emergence, at 14, 28, and 42 days after the onset of giant ragweed emergence, at emergence onset plus 28 days after emergence onset, and a no tillage control treatment. Overall, giant ragweed emerged early, with 50 and 90% emergence occurring on May 12 and 29, respectfully. Temporal patterns of giant ragweed emergence were affected by tillage timing, in that emergence was suppressed the week following tillage. Despite this finding, there were no differences in total giant ragweed emergence across tillage date treatments, indicating that tillage did not suppress or stimulate total giant ragweed emergence. Delaying tillage until several weeks after emergence onset provided greater potential for giant ragweed control, as it allowed a greater percentage of giant ragweed seedlings to germinate and emerge prior to tillage. These results suggest that pre-plant tillage can be used to provide effective control of herbicide-resistant giant ragweed, especially when tillage is delayed at least two weeks after giant ragweed emergence onset.

3.2 Introduction. Giant ragweed has historically been one of the most competitive weeds affecting crop production in the Midwestern United States (Webster et al. 1994). Control of giant ragweed has become increasingly difficult as biotypes of giant ragweed have developed resistance to acetolactate synthase inhibitors and glyphosate (Heap 2016). Managing the weed seed bank with integrated strategies is essential for long-term control of herbicide-resistant giant ragweed. Spring pre-plant tillage and crop rotation are several non-chemical strategies that have been proposed to improve control of giant ragweed (Goplen et al. 2016b). Crop rotations that include alfalfa have been shown to minimize giant ragweed emergence while depleting 96% of the weed seed bank in just two years when weed seed inputs are eliminated (Goplen et al. 2016b). Although alfalfa can be used as an effective tool to manage herbicide-resistant giant ragweed, integrated control options need to be explored for annual cropping systems.

Delayed spring tillage and planting are potential options to improve control of herbicide-resistant giant ragweed in annual cropping systems since giant ragweed is one of the earliest emerging weeds in Midwestern United States crop production (Buhler et al. 1997; Goplen et al. 2016a; Werle et al. 2013; Werle et al. 2014). Previous research has shown that as much as 90% of giant ragweed is emerged by early June in Minnesota (Goplen et al. 2016b). A several week delay in preplant tillage and planting has the potential to improve giant ragweed control without substantially reducing crop yields; delaying corn and soybean planting in the Midwestern United States until late May decreases yields by 15 and 10%, respectively (Van Roekel and Coulter, 2011; De Bruin and Pedersen, 2008). Delayed planting of annual crops such as corn or soybean has been shown to be an effective weed control strategy, and is often a strategy utilized by organic crop producers who do not use herbicides for weed control (Buhler and Gunsolus, 1996; Coulter et al. 2011; Gunsolus 1990; Williams 2009). It is likely that delayed planting can also be an effective tool to combat herbicide-resistant giant ragweed, as it provides the option to utilize tillage or pre-plant burndown herbicides to control giant ragweed prior to crop planting. However, tillage has been shown to stimulate emergence of some weed species, which may limit the capacity of tillage to be used for spring weed control (Bullied et al. 2003; Chauhan et al. 2006). Previous work has suggested that spring tillage with a rototiller does not affect temporal or total emergence of giant or common ragweed (Barnes et al. 2015; Werle et al. 2013). Research has not been conducted to determine how giant ragweed emergence is affected by spring tillage with a field cultivator, which is a more commonly used implement for spring tillage in Midwestern United States row crop production and is much less aggressive tillage with a rototiller. The objective of this study was to evaluate the effect of spring tillage on total giant ragweed emergence and emergence timing to determine its utility as a strategy for integrated control of herbicide-resistant giant ragweed.

3.3 Materials and Methods

3.3.1 Site Description. Replicated field experiments were conducted near Rochester, MN (43.91°N, 92.56°W) and at the University of Minnesota Rosemount Research and Outreach Center near Rosemount, MN (44.70°N, -93.08°W) in 2015. The experiment at Rochester, MN was on a Port Byron silt loam (Fine-silty, mixed, superactive, mesic Typic Hapludolls) with a pH of 7.0 and 4.0% organic matter. The experiment at Rosemount, MN was on a Waukegan silt loam (Fine-silty over sandy, mixed, superactive, mesic Typic Hapludolls). Both research sites had a history of a 2-yr corn-soybean rotation as well as known populations of giant ragweed resistant to glyphosate, Giant ragweed at Rochester, MN was also resistant to acetolactate synthase inhibitor herbicides.

3.3.2 Experimental Design. Experiments at both locations were arranged in a randomized complete block design with four replications and six treatments. The treatments included multiple dates of spring tillage that were determined relative to the initiation of giant ragweed emergence. Treatments included tillage to a depth of 10cm with a field cultivator with 20 cm sweeps spaced 20 cm apart. Treatments included tillage at giant ragweed emergence onset, at 14, 28, and 42 d after emergence onset, tillage at emergence onset plus an additional pass of tillage 28 d after emergence onset, and a no-tillage control. The tillage treatments taking place on giant ragweed emergence onset and at 14, 28, and 42 d after emergence onset occurred on April 28, May 13, May 27, and June 9, respectively at both locations. Two replications at Rochester followed oat (*Avena sativa* L.) that had no fall tillage and the other two replications followed corn that was chisel plowed to a depth of 20 cm in the fall. At Rosemount, all replications followed soybean that was chisel plowed to a depth of 20 cm in the fall. Plots were 3.7 by 6 m at Rochester and 3 by 6 m at Rosemount to accommodate tillage implements. Ten fixed 30 by 30 cm quadrats were placed in two rows through the center of each plot. Emergence was monitored by counting and removing emerged seedlings in each quadrat on a weekly basis, starting at emergence onset and continuing for at least 10 wk or until emergence ceased. Giant ragweed emergence each week was calculated as a percentage of the total. The potential giant ragweed control with tillage was calculated as the total percentage of giant ragweed that emerged at the time of tillage. For the onset plus 28 d post-onset tillage treatment, potential control with tillage was calculated as the total percentage of giant ragweed emerged at the time of the second pass with tillage.

3.3.3 Statistical analysis. The total number of giant ragweed plants emerged, the potential control with tillage, and the percentage of total giant ragweed emerged each week were analyzed using the MIXED procedure of SAS (SAS Institute, 2012). Tillage timing treatment was considered a fixed effect, and experimental location, block (nested within location), interactions, and subsampling were considered random effects. The total number of giant ragweed plants emerged exhibited a skewed distribution, so data were transformed to the natural log scale for analysis and corrected means were back-transformed for presentation. Mean comparisons were made using Fisher's protected LSD at $P \leq 0.05$.

3.4 Results and Discussion

3.4.1 Emergence Timing. Giant ragweed emerged early in the growing season across locations, with an average of 50 and 90% of giant ragweed emergence occurring by May 12 and May 29, respectively. This supports Goplen et al. (2016b), who reported that 90% of giant ragweed emerged by June 4. Tillage timing treatments affected the emergence pattern of giant ragweed by suppressing emergence in the week following tillage at the onset and 14 d post-onset tillage dates (Figure 3-1; Table 3-1). The two-pass treatment with tillage at emergence onset plus 28 d post onset reduced total giant ragweed emergence in the week (May 6) following tillage by 10% compared to the no-tillage control. The treatment with tillage only at emergence onset, however, did not reduce emergence compared to the no-tillage control in the week following tillage. For both treatments with tillage at emergence onset, there were no differences in giant ragweed emergence beyond the first week following tillage.

The 14-d post-emergence onset tillage treatment reduced giant ragweed emergence by 17% in the week following tillage (May 20) compared to the no-tillage control (Figure 3-1). The 14 d post-emergence onset tillage treatment had 8 and 5% greater emergence compared to the no-tillage control in the second (May 27) and third (June 4) weeks following tillage, respectively (Figure 3-1). Tillage likely suppressed giant ragweed emergence the week following tillage due to its influence on germinated but unemerged seedlings. Greater emergence the second (May 27) and third (June 4) weeks following tillage in the 14 d post-onset treatment may have been due to a greater percentage of unemerged seedlings recovering from the tillage disturbance. It is possible that the warmer soil temperatures at later tillage dates allowed a greater percentage of disturbed seedlings to recover and emerge in subsequent weeks. Tillage also reduces soil bulk density near the soil surface, which can increase infiltration of precipitation and allow weeds to emerge from deeper in the soil and may also explain increased emergence in the weeks following tillage in the 14 d post-emergence onset treatment (Buhler and Mester 1991; Chauhan et al. 2006).

The one- and two-pass tillage treatments with tillage at 28 d post-emergence onset did not differ in giant ragweed emergence from the no-tillage control in the first (June 4) or second week (9 June) following tillage (Figure 3-1). The majority of giant ragweed emergence occurred before the 28-d post-emergence onset tillage treatment, which likely limited its effect on emergence since there were fewer unemerged seedlings. The 42 d post-emergence onset treatment, which occurred well after the peak (May 14) of giant ragweed emergence, also did not influence emergence in the weeks following tillage. These results support that late tillage dates do not stimulate additional giant ragweed emergence.

3.4.2 Total Emergence. There were no differences in total giant ragweed emergence among tillage treatments, indicating that tillage timing does not stimulate nor suppress total giant ragweed emergence (Figure 3-2). Although insignificant, the emergence-onset treatment did consistently have the least giant ragweed emergence across locations, which may be related to how the emergence-onset treatment suppressed emergence in the weeks following tillage without having an increase in emergence in subsequent weeks (Figure 3-2). However, earlier tillage dates likely have the greatest potential to reduce total giant ragweed emergence since they coincide with when the majority of giant ragweed seeds are germinating and beginning to emerge. This trend may also be related to the possibility that fewer germinated seedlings recover and emerge following the earlier tillage dates. It is possible that warmer soil at later tillage dates allowed a greater number of seedlings to recover from tillage and thus emerge in subsequent weeks.

This study confirms previous research demonstrating that spring tillage timing does not influence total giant ragweed emergence (Werle et al. 2013). Similar results have also been reported for total emergence of common ragweed, which was unaffected by spring tillage timing (Barnes et al. 2015). Results from these studies, however, differ from those of Buhler (1997), who reported that emergence of large-seeded weeds, including giant ragweed, cocklebur (*Xanthium strumarium*), and velvetleaf (*Abutilon theophrasti*), was greater in tilled conditions versus no tillage. Previous research has shown that tillage generally increases the average weed seedling emergence depth (Buhler and Mester 1991; Chauhan et al. 2006). Tillage may have less of an effect on total emergence of giant ragweed compared to other weeds species since its large seed size allows it to emerge from up to XXX cm in the soil profile even with no tillage (Abul-Fatih and Bazzaz 1979). Weed seed distribution in the soil profile may also influence the effect of tillage on weed emergence, since seed distribution in the soil profile is influenced by past weed seed production and tillage practices, ultimately causing potentially varying results depending on specific field histories (Mohler 1993).

3.4.3 Potential for Control. Later tillage dates had the greatest potential for giant ragweed control with tillage, indicating that delayed tillage and subsequent planting can be utilized as an effective strategy to control herbicide-resistant giant ragweed (Figure 3-3). If tillage is delayed too long, however, weeds may become too large for a single pass of tillage to provide effective weed control (Gunsolus 1990). The optimal timing of spring tillage will maximize giant ragweed emergence while minimizing the weed size. Tillage at emergence onset had the potential to control 15% of total giant ragweed, which was not different from the no-tillage control (Figure 3-3). The 14 d post-emergence onset treatment, which had tillage on May 13, had the potential to control 54% of total giant ragweed, while treatments with tillage at 28 and 42 d post-emergence onset, and onset plus 28 d post-emergence onset, had the potential to control greater than 85% of giant ragweed.

Although weed height at the time of tillage was not documented, tillage dates later than 28 d post-emergence onset were not as effective in controlling emerged giant ragweed, likely because plants were too large for the field cultivator (Figure 3-4). Weed height at the time of tillage was similar for the 14 and 28 d post-emergence onset tillage treatments (Figure 3-4). It is likely that the several week delay in emergence following the 14 d post-emergence onset treatment resulted in similar weed height compared as that at the time of tillage for the 28 d post-emergence onset treatment at the beginning of June. Among tillage treatments evaluated in this study, the 14 d post-emergence onset treatment was likely the ideal tillage for corn or soybean production, as the 2-wk delay in tillage prior to planting provided over 50% control of giant ragweed while minimizing the potential yield reductions of corn or soybean due to delayed planting. The 14 d post-emergence onset treatment also suppressed weed height into June, which would allow post-emergence herbicide applications to be applied to smaller weeds when they are more effective (Carey and Kells 1995) (Figure 3-4). Previous research has shown that when preplant tillage and planting are delayed to allow additional weeds to emerge prior to planting, overall weed densities are reduced, which reduces crop losses due to weeds (Buhler and Gunsolus 1996; Gower et al. 2002; Spandl et al. 1998). Delayed planting has also been shown to require less intensive post-planting weed management, decrease weed control costs, and lengthen the critical period of weed control (Williams 2006). Results from this and previous research indicate that delaying corn and soybean planting until mid-May in the Midwestern United States will likely result in have a minimal effect on crop yield potential, provide over 50% control of giant ragweed, and extend the window for post-emergence weed control operations, allowing improved control of later-emerging weeds.

3.4.4 Conclusion. This study indicates that spring tillage does not stimulate giant ragweed emergence in Minnesota, confirming spring pre-plant tillage as an effective control strategy for herbicide-resistant giant ragweed. The potential control of giant ragweed was greatest for tillage dates 28 d post-onset of giant ragweed emergence or later, as they occurred after the majority of giant ragweed emergence had occurred, while tillage at 14 d post-emergence onset provided 54% giant ragweed control. Giant ragweed emergence was reduced the week following tillage at earlier tillage dates. Reduced emergence following tillage provides additional weed control benefits, such as a longer period of time for post-emergence weed control operations. There were no differences in total giant ragweed emergence among tillage timing treatments, indicating tillage does not stimulate nor suppress total giant ragweed emergence. Additional research should investigate whether earlier tillage dates have potential for less total emergence due to fatally disturbing a greater percentage of unemerged seedlings compared to later tillage dates. This research suggests that delayed pre-plant tillage and planting can be effectively used as part of an integrated plan to control herbicide-resistant giant ragweed without stimulating additional giant ragweed emergence.

Table 3-1. P-value and LSD of the percentage of giant ragweed emerged each week among tillage timing treatments.

	Week									
	4/28	5/6	5/13	5/20	5/27	6/4	6/9	6/16	6/23	6/30
P-value	0.30	<0.01	0.07	<0.01	0.02	0.01	0.07	0.99	0.05	0.24
LSD (%)	6.2	5.3	4.5	4.7	6.3	4.7	2.5	1.6	0.9	0.6

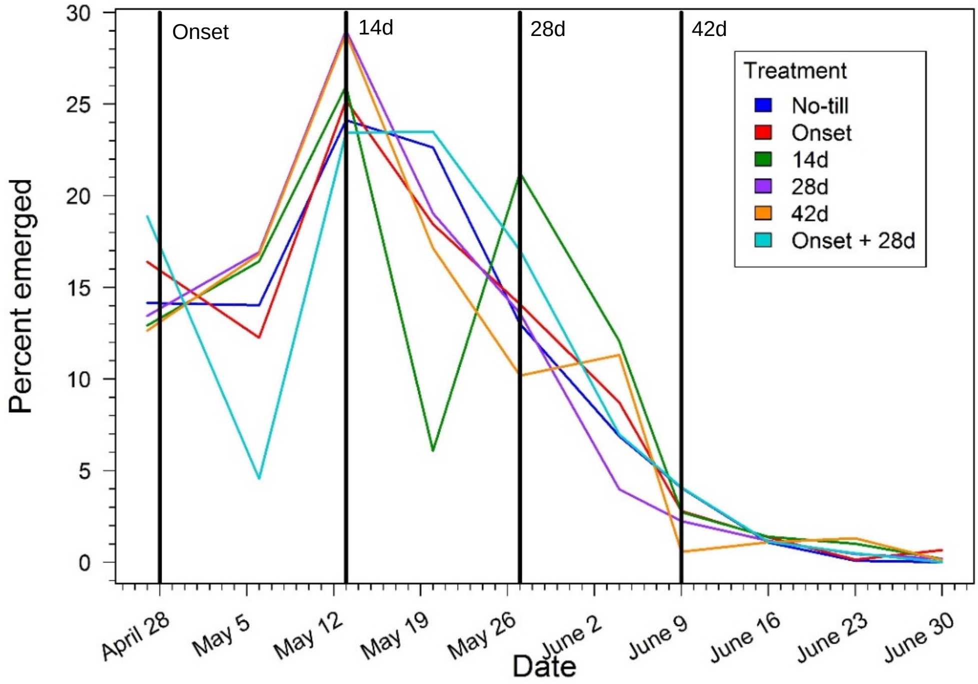


Figure 3-1 Percentage of giant ragweed emerged each week by tillage timing treatment, averaged across locations. Vertical lines represent dates when spring tillage occurred.

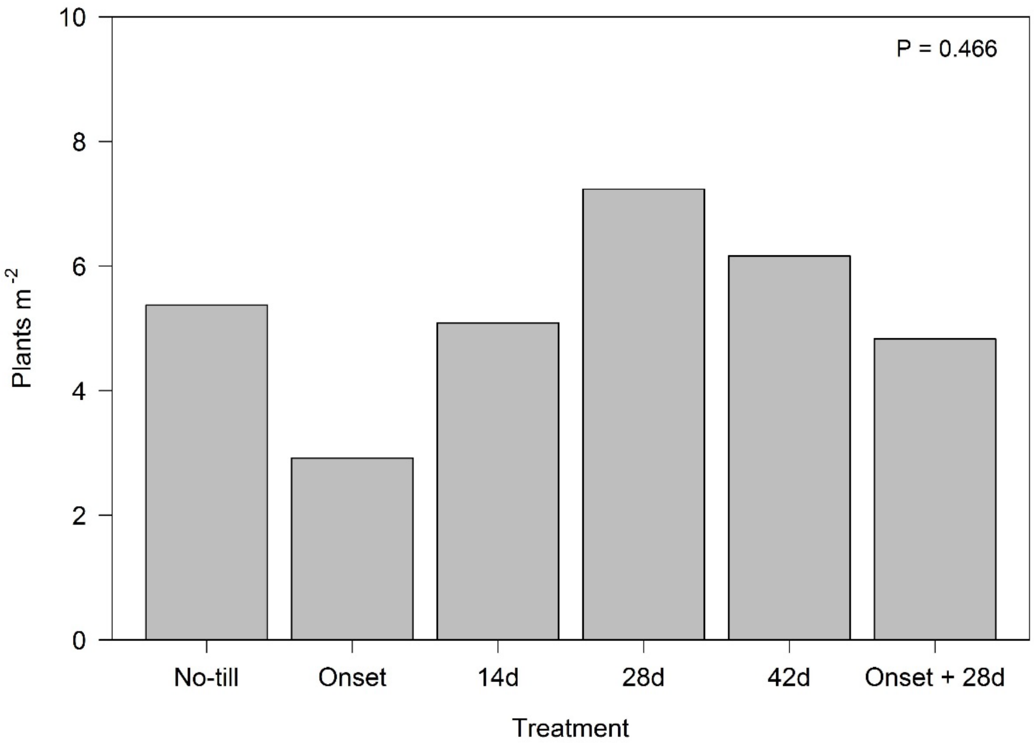


Figure 3-2. Total emergence of giant ragweed in each tillage timing treatment, averaged across locations. Statistical analysis based on natural logarithm transformed data and back-transformed means are provided.

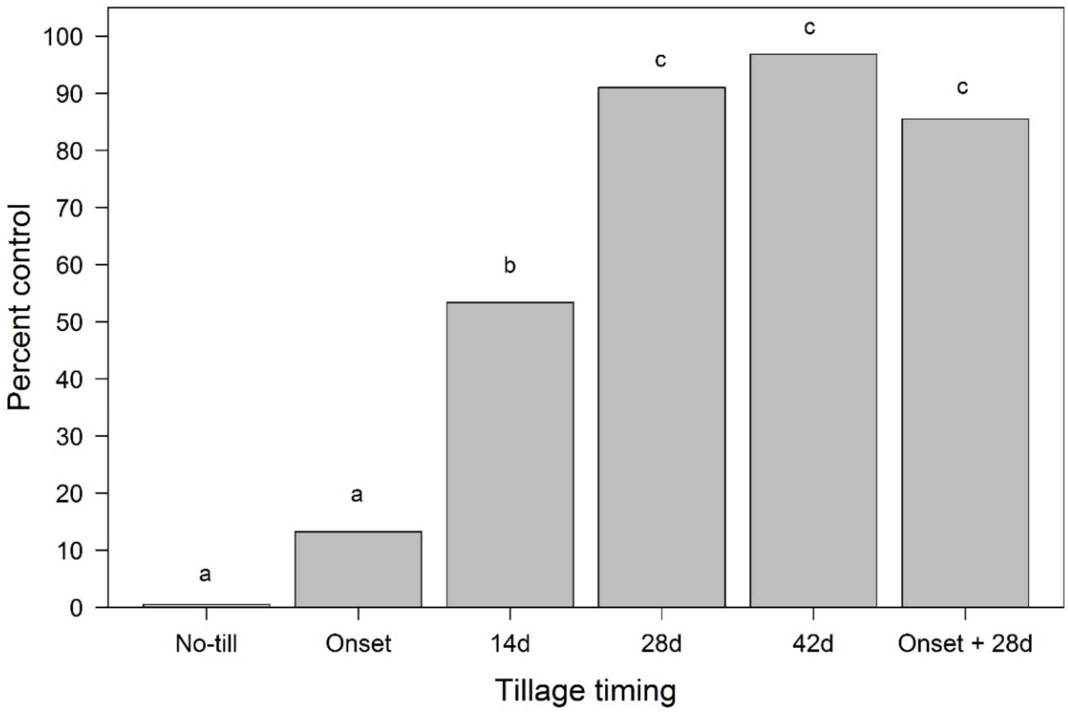


Figure 3-3. Potential for control of giant ragweed at each tillage timing treatment averaged across locations. Bars with different letters indicate they are significantly different according to Fisher's protected LSD test ($P \leq 0.05$).

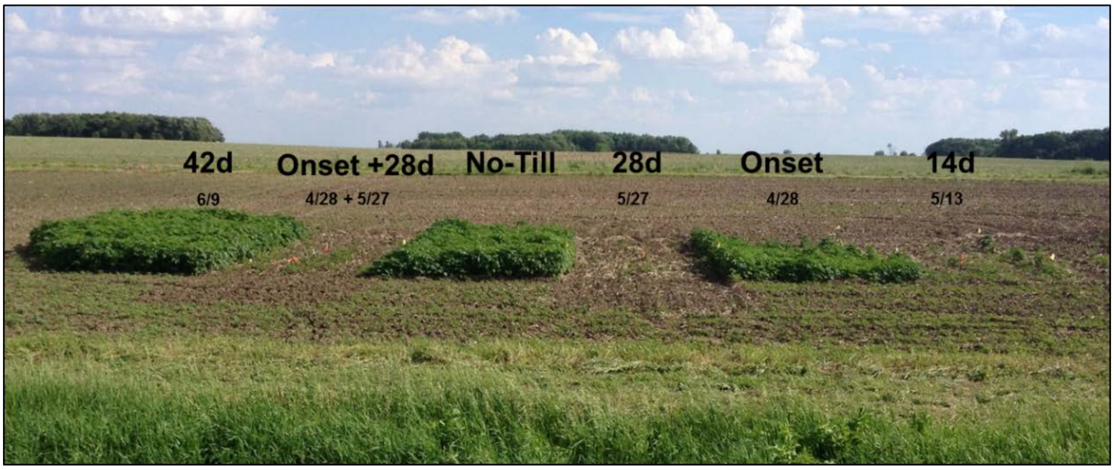


Figure 3-4. Photo of one replication at the Rochester, MN experiment on June 9, 2015, immediately before the 42 d post-emergence onset tillage treatment. Text on photo corresponds to the tillage timing treatment and date of tillage.

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